Automatic assessment of time-lapse OCT for dosimetry control of selective retina therapy

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Motivation and Goal

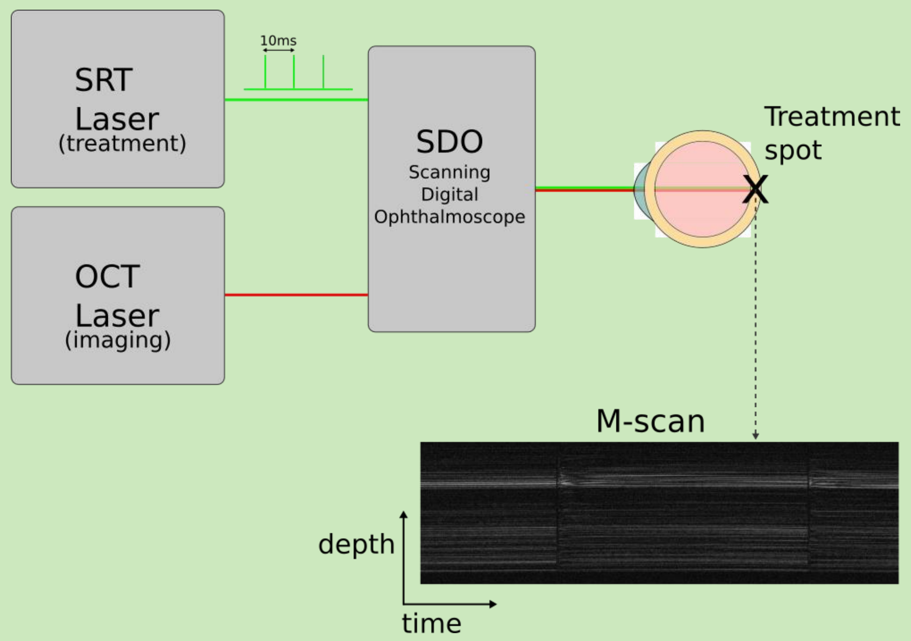
The goal is to use OCT Mscans acquired during Selective retina therapy (SRT) in order to evaulate the treatment energy level. SRT as a laser treatment targets the funduscopically invisible RPE layer of the retina. It is therefore impossible to assess the treatment energy while it is applied. OCT offers the depth information necessary to monitor the RPE response to the SRT laser application.

Materials and Methods

1. Data acquisition setup

SRT: frequency-doubled Nd:YLF laser with pulse width of 250 ns, pulse repetition rate of 100 Hz for 30 pulse-trains

OCT: line scan frequency of 70 kHz, spectral bandwidth of 170 nm centered at 830 nm.



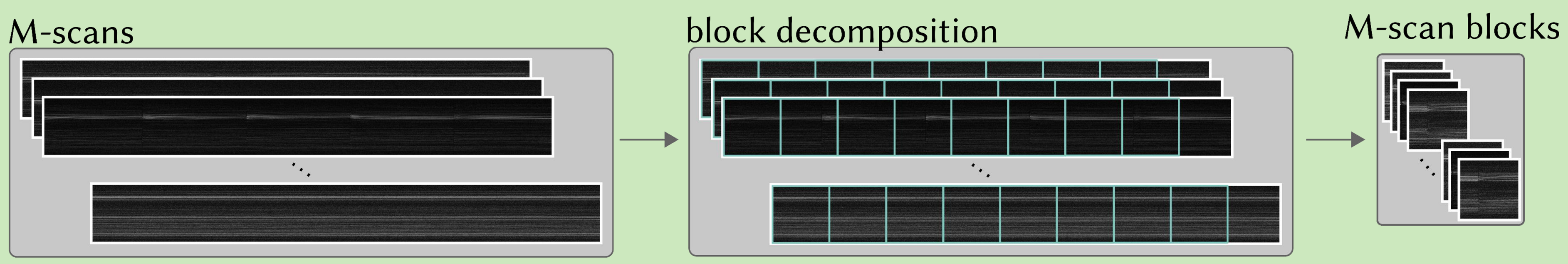
➔The two beams are aligned through an SDO and targeted to the retina.

➔The resulting image is a depth profile of the treatment spot over time (an A-scan per time point).

2. Data description

- 153 enucleated ex-vivo porcine data
- 14 human patient data

Mscan size: (400) × (~ $20K$) px ⟶ divided into square blocks (400 × 400)



Block labelling:

- M, total number of M-scans
- B the number of blocks per M-scan,

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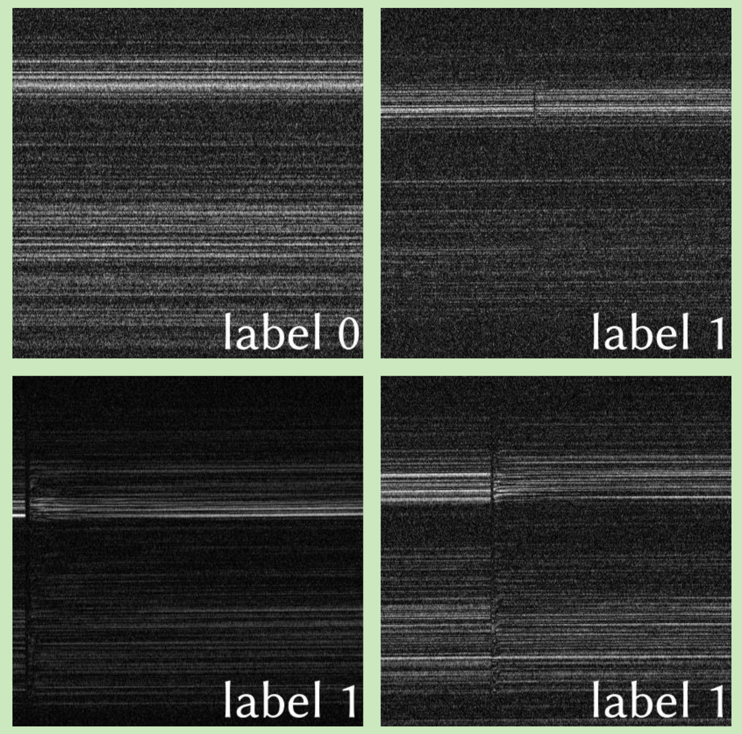
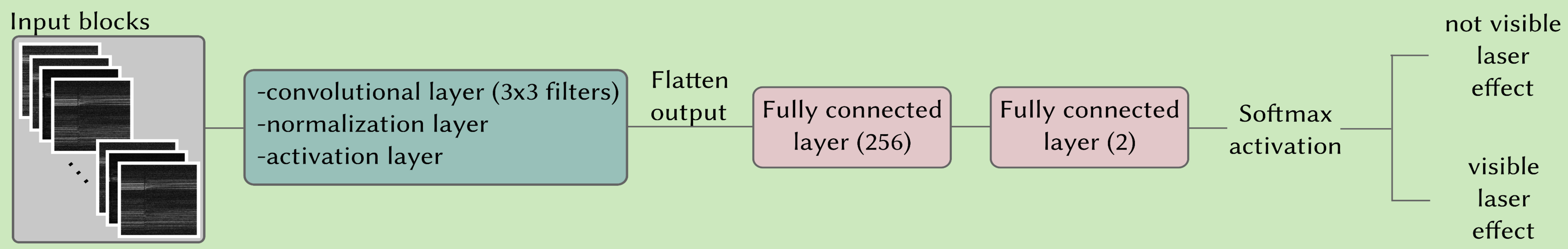
set of $M \times B$ blocks, each with a corresponding label $y_{mb} \in \{0,1\}$

$$y_{mb} = \begin{cases} 0, & \textit{no visible SRT laser effect in block} \\ 1, & \textit{visible SRT laser effect in block} \end{cases}$$



3. Block classification



A convolutional neural network[1] is trained to classify the blocks, according to whether they contain a visible laser pulse or not.

Each block goes through multiple filtering stages, and a decision is made as to what class it belongs to.

The model is first trained on the porcine data, and tested on the human data.
Then, the model is trained on the porcine data, fine tuned with a part of the human data, and tested on the rest human data.

Results

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1. Porcine data classification performs very well
2. Training only on human data
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   Overfitting due to lack of data
3. Model trained on porcine data and tested on human data
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   Good performance
4. Train model on porcine data + finetune using human data
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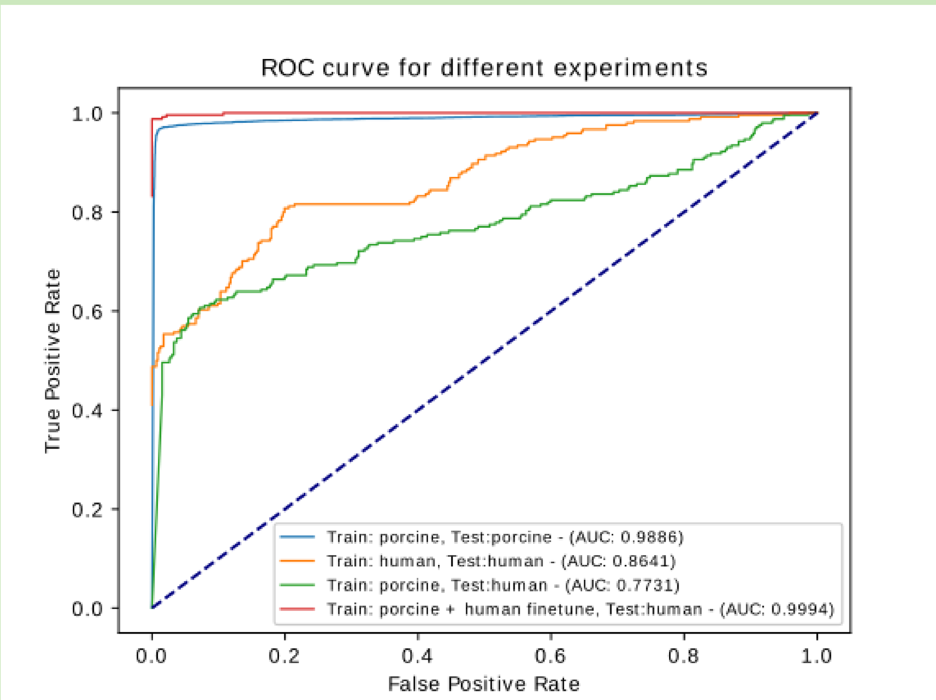
   Significantly increased performance



Conclusions

- Automatic identification of a laser effect on a short Mscan block
- Robust model, able to generalize from porcine to human data

The block level assesment can be used as a first step to evaluate SRT energy treatment, and therefore be part of a dosimetry control system. The porcine data can be used to enrich the model, since they are much easier to acquire.

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[1] He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.* 2016.